MODESTO – A MULTI-OBJECTIVE DISTRICT ENERGY SYSTEMS TOOLBOX FOR OPTIMIZATION

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Abstract – Optimization of district energy systems (heat, electricity and gas) is an important part of the evolution towards a more sustainable energy system. It can be used to support short- and long-term decisions and it leads to further insights regarding the behaviour of the energy system as a whole, resulting in better integration of intermittent renewable energy sources (RES). However, optimization of these energy systems is not trivial, due to large-scale systems, a broad range of time constants, nonlinearities, etc. Additionally, the requirements of the optimization model are very case and goal specific. To facilitate these optimizations, *modesto* – a Multi-Objective District Energy Systems Toolbox for Optimization – is being designed, a Python package that allows easy setting up of energy system optimization models, while offering flexibility to customize to specific cases. This paper presents the current state of *modesto*, a case study illustrating the toolbox's principle and the future expansions that are planned.

1. INTRODUCTION

Climate change and environmental pollution call for a transition to a more sustainable energy system. This energy system will most likely be a multi-carrier energy system, where electricity, gas and thermal networks work in unison. However, the separate development and operation of these energy subsystems is already challenging, let alone the joint development and operation. In this context, this paper presents modesto – a Multi-Objective District Energy Systems Toolbox for Optimization, see Figure 1. As the name indicates, it is a toolbox that provides optimization tools for district energy systems, although in its current state it focuses on thermal systems.

Figure 1: The logo of modesto

When developing such a toolbox it is imperative to be aware of existing energy modelling and optimization tools. Overviews of existing tools have been made by Connolly *et al.* (2010) and van Beuzekom, Gibescu, and Slootweg (2015). The reviews show that many tools are already in existence. However, each of these tools considers different parts of the energy system (electrical, thermal, multi-carrier etc.), and uses different techniques (including simulation or operational optimization) on different time and geographic scales. However, concerning tools that resemble *modesto* (optimization of district energy systems, with a focus on thermal systems), few equivalents can be found: according to Connolly's overview, only the following optimization tools have a similar goal:

- *COMPOSE* (Aalborg University n.d.) is a free modelling tool for multi-carrier energy systems to assess whether energy projects can support RES intermittency. One of its strengths is its ability to take into account uncertainty, and is hence, suited for risk and uncertainty analyses.
- *energyPRO* (EMD international A/S n.d.) is a commercial modelling tool for techno-economic design of multi-carrier energy projects. It focuses on cogeneration or trigeneration, which can be used in combination with district heating.
- *HOMER* (HOMER Energy LLC. n.d.) is a commercial tool that focuses on optimization of micro hybrid electricity systems. Although capable of modelling district heating (in a limited way), its focus is mostly on the electricity system.

Beyond Connolly *et al.*'s overview, the following energy modelling tools seem relevant as well:

- *OSeMOSYS* (Howells et al. 2011) is a systems optimization model for long-run energy planning. The focus seems to be on the electricity system, although heating is included in the output streams. Welsch *et al.* (2012) expanded the OSeMOSYS environment to be compatible with smart grid optimization.
- *JModelica* is a Modelica-based open source platform for optimization, simulation and analysis of dynamic systems (Modelon AB 2017) and has been used on at least one occasion for operational optimization of district heating and cooling systems (Schweiger et al. 2017).
- *DER-CAM* or Distributed Energy Resources Customer Adoption (Stadler et al. 2014; Steen et al. 2015) is a MILP-based optimization tool to support investment decisions in energy systems including distributed energy resources. The objective is to minimize carbon emissions and annual costs for customer site systems or micro grids.
- *oemof* (oemof Developing Group 2017) is an open source optimization platform for multiple energy

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carriers. It is able to connect multiple regional energy systems and has flexible time steps.

- *MODEST*[2] (Model Optimization of Dynamic Energy Systems with Time dependent components and boundary conditions) was developed as a linear optimization tool to find the optimal operation of energy systems from a cost perspective (Åberg and Henning 2011; Åberg, Widén, and Henning 2012). MODEST is aimed at local, regional and national spatial scales and can handle time divisions flexibly.
- *Urbs* (Dorfner 2016, 2017) has the intention to optimize the installed capacity of different types of energy technologies (including storage) in a given energy system, while supplying a specified demand profile. It uses a time step of 1 h, but appears to be intended for a larger geographic scale than *modesto*, although it is flexible to be changed to the needs of the user.

Table 1: The list of symbols

Symbol	Description	Unit
c_p	Specific heat capacity of water	$J\ kg^{-1}\ K^{-1}$
E	Energy use	J
h	Optimization horizon	s
$\dot{m}$	Mass flow rate	$kg\ s^{-1}$
$\mathcal{J}$	Objective function	J or €
$\dot{Q}$	Heat flow rate	W
S	Slack value	J or €
T_{mix}	Mixed temperature	K
T_{ret}	Return temperature	K
T_{sup}	Supply temperature	K
α	Objective weighting function	/ or € J^{-1}
β	Slack penalization weight	/
$\mathcal{C}$	Set of components	
$\mathcal{C}_{out,n}$	Set of components extracting water from node n	
$\mathcal{C}_{in,n}$	Set of components injecting water into node n	
$\mathcal{S}$	Set of slacks	
c	Component index	
n	Node index	
s	Slack index	
t	Time index	

Clearly, the motivation to develop *modesto* does not stem from a lack of energy system optimization tools However, all available tools in their many shapes and flavours do not natively provide the ability to optimize district energy systems with a focus on dynamic behaviour of thermal system components, except for Schweiger at al's work (2017) with *JModelica*, although it should be noted that *JModelica* is unable to solve mixed integer linear problems, which is where *modesto* comes into play.

modesto is a package that, given a network topology, allows easy setting up of optimization problems for district energy systems, although it is limited to district heating at the moment. *modesto* contains models for different typical components found in district energy systems (such as energy storage, energy conversion and energy transportation systems). Often, goals and cases require different models putting emphasis on different dynamics. For this purpose, *modesto* provides different models for the same type of component.

The toolbox is still under development, with the current focus going to district heating systems, but the eventual goal being multi-carrier energy systems. Thus, this paper mostly discusses the tool in the context of district heating.

This paper presents the current status of *modesto*. More specifically, Section 2 discusses the structure of the toolbox, presenting the different component models and the way they are interconnected. Section 3 presents possible applications for *modesto*, while Section 4 shows an example case study. Section 5 discusses possible further developments and, finally, Section 6 concludes this paper. All symbols used in this paper are listed in Table 1.

2. STRUCTURE

This section gives an overview of the *modesto* structure. Firstly, the toolbox is considered as a black box, with the discussion only focusing on the in- and outputs of the toolbox. Secondly, the internal structure of the toolbox is presented in more detail, with first a general overview, followed by a more detailed look at the separate district heating network components and optimization objectives.

2.1 In- and outputs

An overview of all in- and outputs of *modesto* is shown in Figure 2.

A first input is a NetworkX object (Hagberg, Schult, and Swart 2008), describing the configuration of the energy network by using a graph consisting of nodes and edges. Applied to a district heating network, the nodes represent points in the network where a customer, heat source and/or thermal energy storage (TES) system is/are connected to the network or where two or more pipes intersect. The edges connect the nodes and represent the district heating pipes. This input gives *modesto* all required information about the topology of the network and enables the toolbox to set up the network's model.

A second input allows changing the optimization settings. At the moment this includes:

[2] Any similarity between the names of MODEST and *modesto* is purely coincidental; the authors only found out about this existing tool later. Although both are energy optimization tools, *modesto* is aimed at being more flexible towards multiple energy optimization problems, while confining itself to district scale.

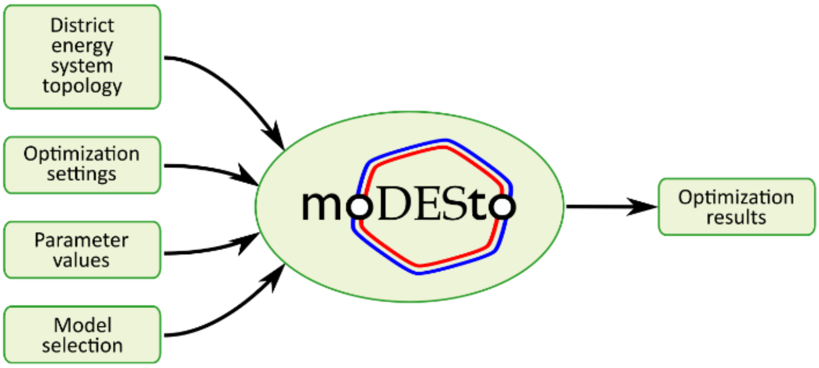

Figure 2: A black-box overview of modesto

Box 1: List of the main assumptions and limitations of the current status of *modesto*.

1. The network is assumed balanced, i.e. the mass flow in a component's supply and return line are always the same.
2. No pressure drops are considered. Hence, only tree shaped networks without loops can be optimized.
3. All component models and the resulting network model are linear, resulting in either a linear program (LP) or a mixed integer linear program (MILP).
4. Building substation models are modelled in a very simplified way, with the temperature differences across the heat exchanger assumed to be known and constant.

- *The selection of the solver*: All solvers that are compatible with Pyomo (Hart et al. 2017) are possible. Currently, the standard solver is set to Gurobi (Gurobi Optimization Inc. 2016), which is used with an academic license. However, tests with CPLEX (IBM Corp. 2016) are being carried out with similar results.
- *The optimization horizon*: This time horizon determines the time period for which the optimization is carried out. It can range from a short-term optimization, generally used for optimal control to long-term optimization, generally used for optimal design.
- *The time step*: *modesto* generates discrete models of district energy systems. The time step setting determines the discretization of the problem.
- *The objective*: Several standard objectives are already available, including minimization of energy and cost, CO_2 and return temperature. It can be extended to primary energy use, share of RES…

A third input sets the parameters values of the optimization problem. Using this input enables the user to easily change e.g. the dimensions of a component, which is useful in optimal design. Another possibility is to change the disturbances to the energy system, such as weather predictions, or boundary conditions such as electricity prices, which is mostly relevant if the optimization is used in a control context with a moving horizon (see Section 3).

A final input allows changing the model selection. As discussed in Section 2.3, some component models differ in the assumptions that are made, leading to a model library.

modesto's goal is to optimize an energy system. Hence, the main output of the toolbox is the optimization's result. *modesto* incorporates a function that provides easy access to all results. In the future, extra plotting functions will be added to visualize results facilitating easy analysis. However, when analysing the results, it is important to realize the assumptions made within *modesto*. Therefore, a short overview of the main assumptions is given in Box 1.

2.2 Internal structure

Using the inputs as they are shown in Figure 2, *modesto* sets up the optimization problem of the given network automatically. The Python package Pyomo (Hart et al. 2017) is used as compiler and the Python package pandas (McKinney 2010) handles data (such as weather and prices).

Given the network topology (the NetworkX object), *modesto* composes the whole optimization problem. Firstly, all component and edge models (heat users, sources, storage and pipes) are built, depending on which model types were selected by the user. These models have a structure as shown in Figure 3. Each component has a return and supply temperature and mass flow rate, with the relationship between them determined by the component model.

Subsequently, *modesto* creates all node models, which describe the interconnections between the components. An example is shown in Figure 4, where a node with four components is shown. Figure 4 also shows the conservation equations contained in a node model. *modesto* does not consider pressure drops (yet), hence the only relevant conservation equations are mass - Eq. (2), and energy - Eq. (3) till (6).

These node models create interconnections between all components, leading to a single model for the entire district heating network.

2.3 Component models

The main components in a district heating network can be split in four groups: 1) those that create a heat demand, 2) heat sources, 3) thermal energy storage systems, and 4) network pipes. A short overview of the models available in *modesto* is given below. The main assumptions that are made in these component models are listed in Box 1.

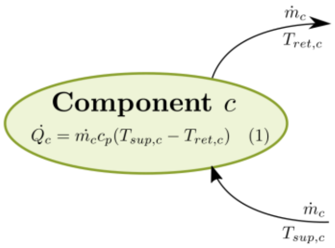

Figure 3: An example illustrating the component model structure.

Regarding components that represent a heat demand, two models have been implemented. A first model, is a simple fixed profile that describes the deterministic heat extracted from the point in the network to which it is connected. This model is presented in Figure 3 (using assumption 4 in Box 1). A second model is an equivalent resistance-capacitance (RC) model describing the building's dynamics. This model creates the possibility to use the building's thermal inertia as a thermal energy storage system which can be used to create extra flexibility. These models are based on the work of Reynders, Diriken and Saelens (2014) and Protopapadaki, Reynders and Saelens (2014).

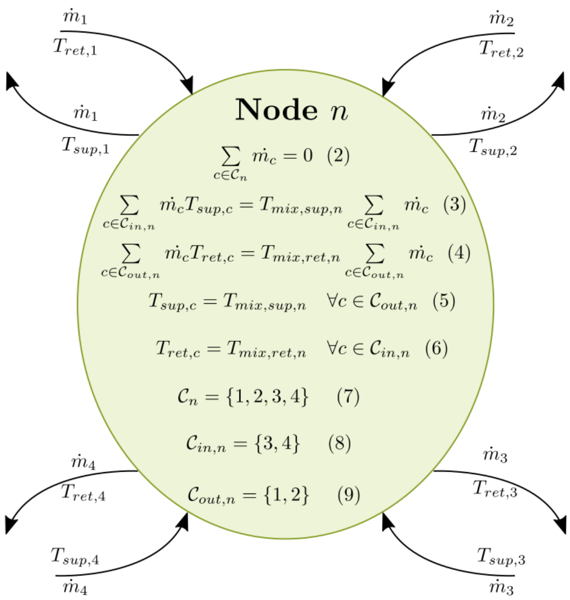

Figure 4: The structure of the model describing a network node.

Two heat source models are available at present. The first model can have limitations on maximum power, ramp rate and efficiency (or COP). If none of these limitations are activated, it is an ideal heat source. The second model is, similar to the heat demand models, a fixed profile, i.e. the heat injection at this point in the network is known in advance. It can be used to model e.g. solar thermal collectors assuming weather predictions are perfect and there is no curtailment. Heat profiles for solar thermal collectors (van der Heijde et al. 2018) are available in *modesto*.

Regarding thermal energy storage systems, a stratified storage tank model (Steen et al. 2015; Vandewalle and D'haeseleer 2014) has been implemented. The model assumes perfect stratification at a fixed high and low temperature. Mass flow rates in and out of the tank can be constrained.

Three pipe models have been implemented in *modesto*, each differing in the assumptions that are made, making them suitable for different applications. A first, very simple model is a perfect pipe, with no heat losses, mass flow limits nor time delays. A second model has limits on mass flow rates and heat losses, but is based on steady-state assumptions and hence requires constant temperatures (van der Heijde, Aertgeerts, and Helsen 2017). A third pipe model, based on Benonysson's node method (Benonysson 1991) no longer requires steady-state assumptions and constant temperatures and is hence suited to analyse time delays in the network. However, to ensure the linearity of the problem in this case, the mass flows in the network need to be known perfectly in advance. This can be ensured by using fixed heat demand models only.

2.4 Objectives

Different objectives have been implemented in *modesto*, including energy use, operational energy cost, CO_2 emission and return temperature minimization. These objectives are set up in the following way.

Firstly, the objective in each component is defined. Taking for example energy and cost optimizations: a heat source has in both cases the following objective:

$$\mathcal{J}_c = \sum_{t=1}^{h} \alpha_{c,t} E_{c,t} \tag{10}$$

With $\mathcal{J}_c$, the component's contribution to the overall objective, $\alpha_{c,t}$ equals 1 in case of an energy optimization or equals the heat source's energy price [€/$\text{kWh}_{\text{primary}}$] in case of a cost optimization. $E_{c,t}$ is the heat source's primary energy use during time step t.

Other possible contributions to the objective include the slacks, which are optimization variables that are added to inequality constraints for robustness. The value of all slack variables is integrated in the objective function using a penalization weight β in order to discourage the use of these slacks, leading to the following expression for the problem's objective:

$$\mathcal{J} = \sum_{c \in C} \mathcal{J}_c + \beta \sum_{s \in \Omega} S_s \tag{11}$$

3. POSSIBLE APPLICATIONS

modesto is designed in such a way that it can be used for different goals and can be easily implemented within other tools. Two possible applications are shortly presented here, with a description on how *modesto*, designed to solve an optimal control problem, could be used.

3.1 Model predictive control

Optimal control has already been used often in the literature to reduce the district heating network's operational costs (Benonysson, Bøhm, and Ravn 1995; Korpela et al. 2017) or to provide demand side management to integrate RES (Salpakari, Mikkola, and Lund 2016). However, optimal control only correctly tracks the optimal case if there are no mismatches between reality and model and if there are no prediction errors.

To account for these unavoidable errors, model predictive control (MPC) can be used instead. It combines optimal control (*modesto*) with feedback control, applying the optimal control signals to the actual network, as can be seen in Figure 5, regularly recalculating a new optimal control strategy making use of new predictions and measurements. Verrilli et al.'s work is a recent example of an MPC for district heating (Verrilli et al. 2016).

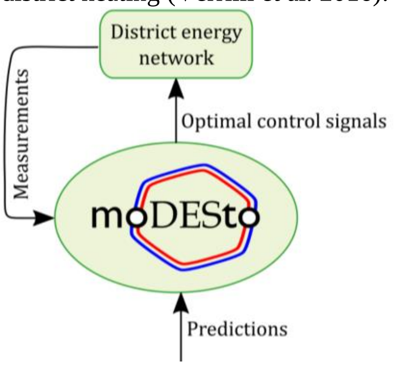

Figure 5: The flow chart of an MPC using *modesto* to control a district energy network

3.2 Integrated optimal control and design

modesto can be used for integrated optimal control and design as well; design parameters are varied throughout multiple runs of the optimal control problem. The variation with the best objective function value is chosen as the best design. The integrated optimal control problem helps to provide a fair basis of comparison for various designs, whereas a control based on simpler rules might fail to do so. A flow chart describing the integrated optimal control and design process is shown in Figure 6.

4. A CASE STUDY

This section shortly presents a case study to illustrate the possibilities of *modesto*.

4.1 Case description

The case considers an imaginary district energy system consisting of three residential areas, connected by a thermal network and heated by a central heat production plant (e.g. ORC plant fed by geothermal energy). This configuration is considered as the base scenario. As a future scenario, a large solar thermal collector array is added. To get the solar fraction as high as possible, large TES tanks are added at the solar array network node. Furthermore, to make the (backup) central heat supply as constant as possible (which is beneficial to e.g. a geothermal ORC plant which requires a stable output power), a short-term storage tank is added near the backup plant.

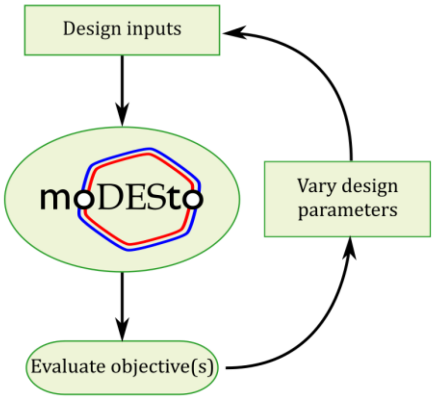

Figure 6: Flow chart describing the integrated optimal design and control process using *modesto*.

The lay-out of the network is shown in Figure 7, with the extension for the future scenario in dashed lines. All optimization runs consider a horizon of a full typical meteorological year with a time step of 6 h. For actual modelling purposes, this is a large time step, but this choice was made for the sake of a quick showcase and comparison. The modeller can freely choose the time step.

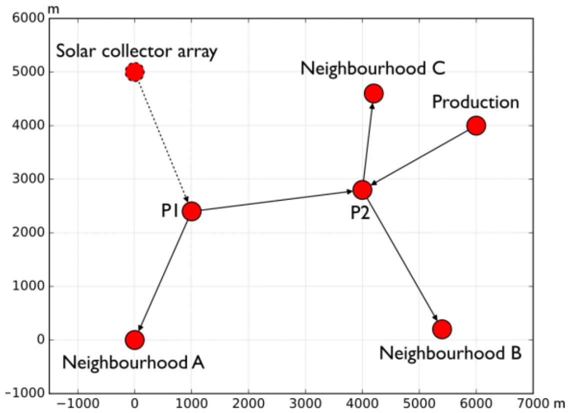

Figure 7: Lay-out of the case study. Base scenario in full lines and circles, future scenario extension dashed.

For both scenarios, the same weather input profiles are used, as well as the same heat demand for the neighbourhoods. These profiles are shown in Figure 8. The design parameters considered for both cases are summarized in Table 2. The total annual space heating and domestic hot water energy demand of the neighbourhoods is 185 GWh/a. The thermal network is operated at a supply and return temperature of 70°C and 30°C, respectively.

4.2 Base scenario

The base scenario considers the existing neighbourhoods with a single heat generation plant at node "Production" and limited short-term TES tank at the same location. The storage buffer near the heat generation plant is effectively used as a short-term storage. The evolution of its state of charge (SoC) varies rapidly, and is hence not shown on a separate graph. The heat input profile from the central heat generation plant (at node "Production") is shown in Figure 9. In this case, the central heating plant is sized according to the minimum nominal power needed for the year optimization, by iteration. Apart from the slight attenuation by the short-term storage tank, the heating profile follows the load variations (Figure 8 – bottom). In total, 199.5 GWh/a of heat has to be injected into the network.

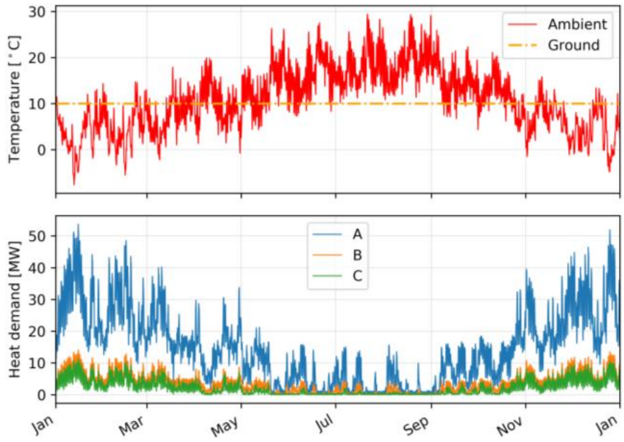

Figure 8: Ambient ground input temperature profiles (top) and heat demand per neighbourhood (bottom).

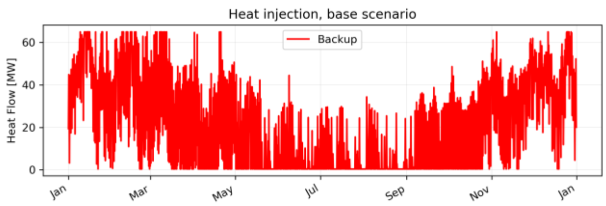

Figure 9: Heat injection from central generation plant in the base scenario.

4.3 Future scenario

In the future scenario, a large solar thermal collector array of 300 000 m^2 is added at the node "Solar Collector Array". A large seasonal TES pit is built at the same location. Additional long-term storage tanks are installed at neighborhoods A and C. The heat injections from the solar thermal collector (STC) array and the backup heating plant are shown in Figure 10. In this system, 93.2 GWh/a of backup heat (from the central production plant) is still needed.

Figure 11 shows the evolution of the energy stored in all of the TES systems. For the seasonal storage systems, the seasonality is clear. These tanks are discharged during winter, and recharged during summer. The short-term storage tank shows a lot more charge/discharge cycles in the SoC diagram, but due to the limited capacity of the tank this is barely distinguishable on the energy diagram (Figure 11 – top).

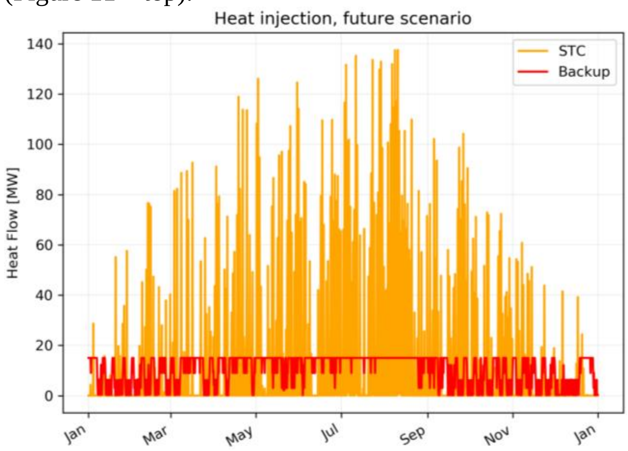

Figure 10: Injection of heat by the solar thermal collector (STC) array and the backup heating plant in the future scenario.

4.4 Comparison

Two scenarios were chosen, using very similar network lay-outs, to illustrate that modesto is a very flexible tool that allows calculating various cases with only limited code changes. The addition of the new network node with

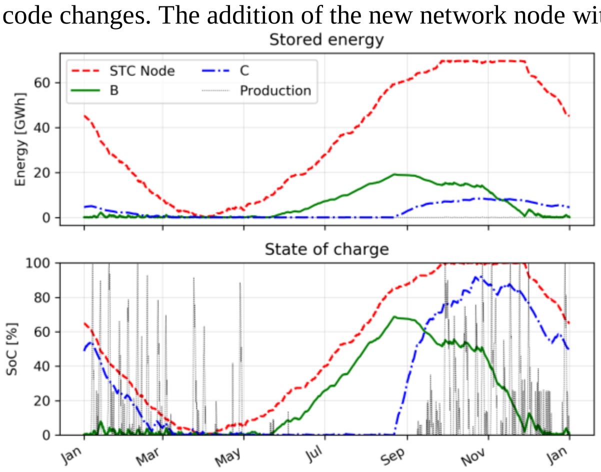

Figure 11: Evolution of stored energy (top) and state of charge (bottom) of the various storage systems in the future scenario.

the solar thermal collectors is accomplished with two extra lines in the network configuration code; another 5 lines are added to configure the parameters of the two added systems. Adding storage in an existing node only requires changing the dictionary of components in those nodes in the NetworkX input, and adding few lines for the parameters again.

The chosen scenarios led to a MILP problem. To solve the future scenario for a full year until a MIP optimality gap of around 1.8 % (best feasible solution found) takes not more than 60 seconds on a Dell Latitude E7470 device

Table 2: Design parameters of system components for the base and future scenarios.

Node	Component	Base scenario	Future scenario
Solar collector array	STES	/	1 500 000 m^3
	STC array	/	300 000 m^2
Production	Heat generation plant	65 MW	15 MW
	Short-term storage tank	3000 m^3	3000 m^3
Neighborhood A	STES	/	600 000 m^3
Neighborhood B	STES	/	200 000 m^3

with an Intel® Core™ i7-6600U 2.60 GHz with 2 cores (4 logical processors); the device has 16 GB RAM and runs Windows 10 as operating system. The base scenario can be reduced to a linear problem (all binary variables presolved) with negligible solution time.

5. FUTURE WORK

modesto is still a work in progress, with many plans for possible expansions. What follows is an overview of the most important planned expansions.

As already mentioned, *modesto* is meant for district energy systems in general, though currently it only focuses on district heating. Hence, in the future, multi-carrier energy systems will become possible as well. Additionally, extra objectives will be added, with the possibility to combine multiple objectives with weights.

The assumptions in Box 1 give an indication of other planned expansions, including non-linear optimization, pressure drops in the network and unbalanced networks.

Furthermore, extra components will be added, being mainly extra heat source models for e.g. CHP's and heat pumps, and extra thermal energy storage systems, such as borefields, aquifers, phase change materials (PCM), etc.

Finally, to simplify the use of *modesto*, methods to plot the optimization's results will be developed and an extensive documentation will be made.

6. CONCLUSION

This paper gives an overview of *modesto*, a toolbox for the optimization of district energy systems, designed in such a way that it can easily be used for different goals and cases. Both the interface and internal structure are presented in detail. Additionally, a short overview of implemented component models and objectives is given.

To illustrate possible uses of *modesto*, a case study is presented and analysed which confirms *modesto's* flexibility in handling changes in design and inputs. A conventional district heating scenario is compared to a future case with a large ratio of solar thermal input and large seasonal energy storage systems.

Finally, the future plans are elaborated on, the main ones being an expansion from district heating systems to multi-carrier energy systems (including the electricity system), and introducing more component models, both for new components that are not included yet, and new models for components already included but modelling different/ more/less dynamics.

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